Optics Communications 433 (2019) 126–131

Contents lists available at ScienceDirect

Optics Communications

journal homepage: www.elsevier.com/locate/optcom

Imaging through scattering media via support vector regression

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A R T I C L E I N F O

Keywords:
Imaging through scattering media
Speckle
Computational imaging
Inverse problems

MSC:
00-01
99-00

A B S T R A C T

A clear image of observed object may deteriorate into an unrecognizable speckle pattern when encountering with heterogeneous scattering media, thus it is necessary to recover the object image from the speckle pattern. Here, a machine-learning-based support vector regression (SVR) method for imaging through scattering media is experimentally demonstrated. The proposed method learns inverse scattering function (ISF) with known object-and-speckle pairs, then reconstructs unknown object with the learned ISF. Essential normalization preprocessing is pre-performed before learning the ISF. Experiments show that more training pairs lead to more accurate ISF and higher reconstruction fidelity. The proposed method provides a general solution for imaging through scattering media and is expected to has its potential applications on inverse problems, such as phase retrieval.

1. Introduction

Imaging through scattering media or scattering image reconstruction has been a hot research topic in the fields of physics and biomedicine [1–8]. Many methods have been proposed to reconstruct object images from scattered speckle patterns. Some methods need a phase shift interferometry or a complicated calibration process to obtain the transmission matrix (TM) of scattering media, which are based on the random scattering theory [9–14]. Phase-retrieval based methods utilize the principle of optical memory effects to translate the inverse scattering problem into phase retrieval problem [15–17]. But phase retrieval algorithms are always dependent on the initial points (so needs to restart several times to obtain a satisfying reconstruction) and noise sensitive (since noise would pollute the measured speckle pattern and introduce bias to Fourier amplitude of object image). Ghost imaging can retrieve the information of an unknown object without a spatial-resolving detector towards it, while a reference beam is necessary and sometimes a calibration is needed [18,19]. To some extent, this limits the fields that the approaches can be applied to.

Machine learning (ML) has been widely tried to seek for reliable and generalizable solutions to numerous classification and regression tasks [20–25]. In this paper, a radial basis function based support vector regression (RBF-SVR) method for imaging through scattering media is proposed. The RBF-SVR method learns the inverse scattering function (ISF) of a scattering system with a known dataset containing numbers of object-and-speckle pairs (OS pairs in short). The imaging capability is not only validated on images inside the dataset, but also objects outside the dataset. Performances under different signal-to-noise ratios (SNRs) are evaluated through simulation. Relationship between reconstruction fidelity and number of training OS pairs is also analysed. Experiments show that the proposed method learns the ISF well and can be used for imaging through scattering media. And, the proposed method is noise robust to some extent. Besides, more learning pairs lead to more accurate ISF and higher reconstruction fidelity. With the help of RBF-SVR, scattering image reconstruction can be realized without knowing the exact principle of scattering. What is more, the RBF-SVR method can be seen as a generalized solution for inverse scattering and has a promising prospect in inverse problems such as phase retrieval [26,27].

The rest of this paper unfolds as follows: The experimental methodology and the mathematical derivation of the RBF-SVR method are presented in Section 2. Section 3 demonstrates relative experimental results and analyses, while conclusions are drawn in Section 4.

2. Methodology

The simplified scattering system was demonstrated in Fig. 1. The spatial light modulator (SLM, used to modulate object images) was illuminated by a laser, then the modulated light changed its direction with a beam splitter (BS in Fig. 1), and travelled through a diffuser (D in Fig. 1, served as scattering media), next the scattered light was captured by an image sensor. The relationship between input object (Object in Fig. 1) and corresponding output speckle (Speckle in Fig. 1) can be described as:

$$E^{out} = f\left(E^{in}\right) \tag{1}$$

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https://doi.org/10.1016/j.optcom.2018.10.008
Received 9 August 2018; Received in revised form 5 October 2018; Accepted 6 October 2018
Available online xxxx
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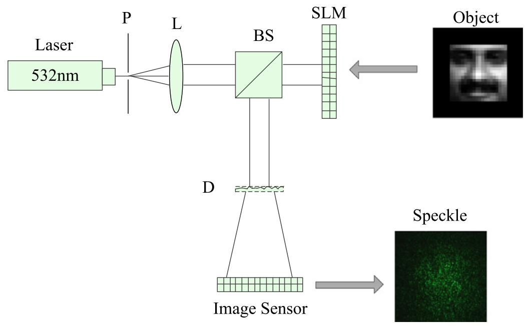

Fig. 1. Experiment schematic of single-layer scattering system. P, pinhole; L, lens; BS, beam splitter; SLM, spatial light modulator; D, diffuser.

where $E^{out} \in R^{M_{out}}$ is the vectorized output speckle pattern, $f(\cdot)$ denotes the forward scattering function (FSF), $E^{in} \in R^{M_{in}}$ represents the vectorized input object image. M_{in} and M_{out} are the pixel numbers contained in input object and output speckle, respectively.

Support vector regression (SVR) is utilized to conduct scattering image reconstruction [28]. The main two parts of SVR are training a model and regressing with the model. Here, the model is the ISF of the scattering system (see Fig. 1), and the regression is the reconstruction of unknown object images. The whole schematic of the proposed method is demonstrated in Fig. 2. To train the ISF, a dataset containing adequate known OS pairs should be established to provide the training data. l_2-*norm* based normalization preprocessing is considered for each captured speckle pattern. With known training pairs, the ISF can be learned column by column. Once ISF learned, image reconstruction can be accomplished immediately. The aim in this paper is to reconstruct the original input object from a given unknown speckle pattern, which can be written as:

$$E^{in} = f^{-1}\left(E^{out}\right) \tag{2}$$

where $f^{-1}(\cdot)$ denotes the ISF to be learned.

The ISF is modelled by solving the following problem:

$$\min_{w,b} \frac{1}{2} w^T w + C \sum_{n=1}^{N} \max\left(0, \left|w^T E_n^{out} + b - E_n^{in}\right| - \varepsilon\right) \tag{3}$$

where w denotes the inverse sensing matrix and follows $f^{-1}(E^{out}) = w^T E^{out} + b$ (b is the intercept vector of ISF), C is a constant parameter trading between regularization and violation, E_n^{out} is the nth output speckle, E_n^{in} represents the nth input object, ε represents a parameter indicating the acceptable error, N is the number of training pairs.

As for any $L2$-regularized linear model, their optimal solution can be represented as linear combination of independent variables. Mapping the speckle space into feature space and the optimal solution of Eq. (3) can be rewritten as $w = \sum_{n=1}^{N} \beta_n \phi\left(E_n^{out}\right)$, where β_n is the coefficient corresponding to nth speckle pattern, $\phi(\cdot)$ denotes a mapping function.

Substituting the solution to Eq. (3) and applying the kernel trick, we obtain: [28,29]

$$\begin{aligned} &\min_{\beta,b} \frac{1}{2} \sum_{n=1}^{N} \beta_n \beta_m K\left(E_n^{out}, E_m^{out}\right) \\ &+C \sum_{n=1}^{N} \max(0, \left|\sum_{m=1}^{N} \beta_m K\left(E_n^{out}, E_m^{out}\right) + b - E_n^{in}\right| - \varepsilon) \end{aligned} \tag{4}$$

where $K(\cdot,\cdot)$ denotes the applied kernel function.

In this paper, the utilized kernel function, radial basis function (RBF), is defined as:

$$K\left(E_n^{out}, E_m^{out}\right) = \exp\left(-\frac{\left\|E_n^{out} - E_m^{out}\right\|^2}{2\sigma^2}\right) \tag{5}$$

where σ is a positive real number.

For comparison, polynomial function based support vector regression (PF-SVR) method is also considered, where polynomial function serves as the kernel function and is defined as:

$$K\left(E_n^{out}, E_m^{out}\right) = \left(a\left(E_n^{out}\right)^T \cdot E_m^{out} + c\right)^p \tag{6}$$

where a and c are real numbers, p is a nonnegative integer indicating polynomial order.

Parameter C in Eq. (4), as well as parameter a, c, p in Eq. (5) and parameter σ in Eq. (6), are all decided by the combination of grid searching algorithm and cross-validation strategy to obtain an optimal ISF [30]. Then with the obtained ISF, by substituting kernel function expressions to Eq. (4) separately and solving it, inverse scattering or scattering image reconstruction can be accomplished. Reconstruction or regression fidelity is evaluated with peak signal-to-noise ratio (PSNR), which is defined as:

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I{}^2}{MSE}\right) \tag{7}$$

$$MSE = \frac{1}{m_x m_y} \sum_{x=0}^{m_x-1} \sum_{y=0}^{m_y-1} \left[E^{in}(x,y) - E_{recon}^{in}(x,y)\right]^2 \tag{8}$$

where MAX_I denotes the maximum possible pixel value of images and $MAX_I = 255$ when pixels are presented in an 8-bit format. m_x and m_y represent the number of pixels of images in x-axis and y-axis, respectively. E_{recon}^{in} means the reconstructed object image with learned ISF. From the definition, it is obvious that higher PSNR value means higher image reconstruction fidelity.

3. Experimental results

Next, experiments were conducted to verify the methodology illustrated above. The wavelength of employed laser is 532 nm. A SLM (HES6001, Holoeye) with resolution of 1920 × 1080 and pixel pitch of 8 μm was used to modulate object images. A 220 grit ground-glass diffuser (DG10-220-MD, Thorlabs) served as scattering media. A CMOS image sensor (C13440-20CU, Hamamatsu) with resolution of 2048 × 2048 and pixel pitch of 6.5 μm was used to record speckle patterns. The CBCL Face Recognition Database (provided by the Center for Biological and computational Learning at MIT) was used to provide face and non-face images [31]. The face images in the Database were collected from different persons. The non-face images were different structured random textures. Each image in the database was enlarged to 20 × 20, *i.e.*, $M_{in} = 400$. We enlarged and modulated images (for training purpose) one by one into the SLM, and collected the corresponding output speckle patterns at the end of the scattering system (showed in Fig. 1), then experimental training OS pairs were generated. Experimental testing OS pairs were generated the same way. For the convenient of training, the pixel number of each output speckle pattern was also sampled to 400, *i.e.*, $M_{out} = 400$. l_2-*norm* based normalization preprocessing was considered for all speckle patterns before learning ISF.

Examples of the training and testing OS pairs were shown in Fig. 3. Objects (see Fig. 3(a) and (b)) travelled through scattering system and only unrecognizable speckles (see Fig. 3(c) and (d)) could be recorded.

In the first experiment, 400 face images of the database were chosen randomly to be input object images of the scattering system (see Fig. 1) to collect their output speckle patterns one by one, to form training pairs. Face images and non-face images were also randomly chosen from the rest of the database to generate testing pairs. With the 400 facial OS pairs, as well as the proposed train-and-reconstruct procedure (see Fig. 2), the ISF could be learned. Once the ISF was learned, given an arbitrary unknown speckle pattern, the reconstruction can be accomplished immediately. The reconstructions of PF-SVR and RBF-SVR were listed in Fig. 4.

In reconstructions of training face images, the averaged PSNR of PF-SVR was 23.7 dB (see Fig. 4(a)) while that of RBF-SVR was 24.2 dB (see

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